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An Improved Method of Flotation Froth Image Segmentation Based on Watershed Transformation

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Abstract. *Watershed transformation is an important method of image edge segmentation. The traditional watershed method is poor in dealing froth image mixed with different sizes of bubbles because single threshold value can't eliminate noises in large bubbles on top and enhance the edges of small bubbles simultaneously. An improved method of froth image segmentation based on watershed transform was proposed in this paper. First, a high-low-hat transformation was done to froth image to increase bubble prominence. Then the markers of catchment basins were searched with different threshold values as to large, medium and small bubble objects. After that, the large and medium-sized catchment basins were morphologically marked and re-shaped. Finally, standard watershed transformation was executed on the target froth image. Experimental results show the proposed method is accurate in marking catchment basins with relatively good robust performance. In contrast to traditional methods, the proposed method is obviously more accurate in edge segmentation of froth image with an accuracy rate of over 80% and the accuracy rate is significantly higher in dealing with complex froth images.*
Keywords: Watershed transformation; Froth image; Edge segmentation; High-low-hat transformation; Marker re-shaping.

Introduction. Froth image segmentation is a method used to distinguish mineral flotation state.[1] Classic image segmentation algorithms are based on the threshold [2], or area [3], or edge [4], etc.. One of the main characteristics of a flotation froth image is of no background, with such phenomena as morph, overlay, adhesion, and so on, thus being suitable for the segmentation based on area expansion.[5]

Watershed transformation is a typical segmentation method based on area expansion, and widely applied in such areas as smart transportation system[6], medical image analysis[7], remote probing[8], etc.. Experts and scholars have tried in many ways to apply the transformation to froth image segmentation, having reaped some benefits[9]. Sadr-Kazemi et al uses it to segment froth images, pointing out that the key procedure is to mark the froth seed area in advance[10]. Shao Jianbin points out the importance of froth marking at proper threshold, which, if too high, will cause under-segmentation, and if too low, will then cause over-segmentation[11]. Yu Wangsheng et al offers an idea of morphologically re-shaping the markers in order to improve the accuracy of marking[12]. Liu Yuqin et al applies high-low-hat transformation to pre-process the froth image so as to enhance its contrast ratio, having thus improved the accuracy of segmentation[13]. All the above-mentioned methods are highly dependent on the size and shape distribution of the froths, being not so good for segmenting froth images mixed with both large and small bubbles. To solve this problem, Hao Hemin et al proposes a threshold self-adjusting segmentation method, which can't fully meet the challenge yet[14].

This paper proposes a newly improved froth image segmentation method based on watershed transformation. With good robustness, the method can be well adopted on the images mixed with both large and small bubbles.

1. Froth Image Segmentation Based on Watershed Transformation.

1.1. The Basic Idea of Watershed Transformation. Watershed transformation is a mathematically morphological segmentation method on the basis of topology, which, basically, takes the image as an topological landscape put upside-down, that is to say, the grey-scale value of every pixel is taken as the altitude, and the gradient information is used to find out the linked areas. The method supposes that the smallest value in a certain area and the areas around the point form a catchment basin, which expands as the water level goes up until it reaches the watershed[15].

The typical watershed transformation is proposed by L. Vincent, including two steps — sequencing and submerging[16]. The watershed means the largest possible value of the input image, which, usually is the gradient image, i.e.,

$$g(x,y) = grad(f(x,y)) = \sqrt{(f(x,y) - f(x-1,y))^2 + (f(x,y) - f(x,y-1))^2} \quad (1)$$

In this formula, $f(x,y)$ stands for the original image, while $grad()$ stands for gradient arithmetic's.

The watershed arithmetic is also an iterative marking process: first, the pixels are sequenced from low to high according to the grey value of each pixel; then, in the process of gradual submerging, the smallest value in each area is judged in the H-minimum area in the order "first in, first out", and the catchment basin is also marked.

1.2. Froth Image Segmenting Method Based on Watershed Transformation. Reverse the froth image, then every bubble becomes a catchment basin, and can be edge-segmented using watershed transformation. As the transformation is sensitive to weak edges, and due to the uneven lighting, noise, quantizing error, inner-area patterns, and so on, which, unavailingly, exist in the image, many partial minimum value will be generated, causing a quantity of tiny areas, i.e., causing over-segmentation.

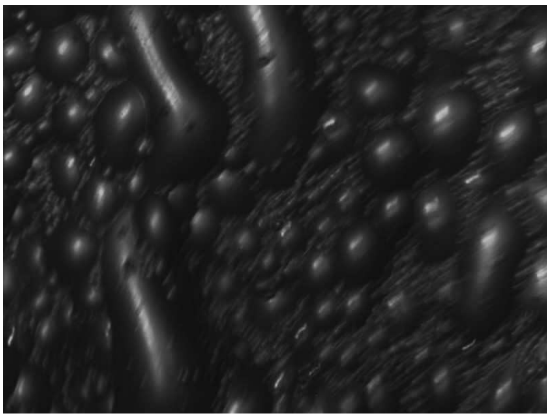

FIGURE 1. A Froth Image

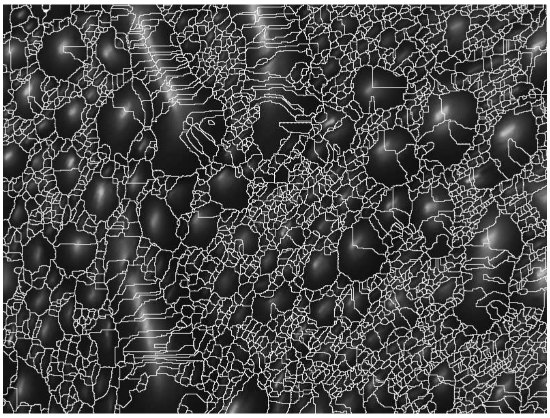

Figure 2. Froth image edge segmentation based on pure watershed transformation

Figure 1 shows a froth image, and Figure 2 shows the results of the edge-segmentation by directly using the watershed transformation. Obviously, there is a very serious problem of over-segmentation.

The basic procedure of froth image segmentation based on watershed transformation is as follows: First, to search for the catchment basin markers via the H-minimum area transformation; Then, to re-construct the catchment basin's marking morphology; At last, to conduct edge segmentation through the application of watershed transformation.

The formula of minimal morphological expansion transformation for foam image is defined as follow:

$$g(x, y) = H\min(f(x, y), h) \tag{2}$$

In formula(2), Hmin() represents minimal morphological expansion transformation; h represents the depth threshold, which is used to eliminating catchment basins.

1.3. **The Optimization of Image Segmentation.** To enhance the segmenting effect of watershed transformation, we can apply the following 3 classical segmenting and optimizing technologies besides a choice of a proper threshold of the H-minimum area.

One way is to change the gradient formula of the froth image so that the catchment basin only corresponds to a froth target in a simple way, i.e., to conduct a threshold operation on the gradient image, i.e.,

$$g(x, y) = \max(grad(f(x, y)), \theta) \tag{3}$$

In formula(3), grad() represents gradient transformation; θ represents the threshold value.

The second way is to increase the contrast ratio of the froth image. According to the research by Gu Yingying et al, the part with a grey value lower than 20 is the inter-bubble shadow, and the part with a grey value bigger than 225 is the reflection of the lighing at the top of the froth[16]. Therefore, we can carry out a high-low-hat filtering morphological transformation of the forth image, making a certain proportion of data distributed at the highest strength while a certain proportion of data distributed at the lowest strength.

Set the grey value of $a\%$ pixels is over u, the grey value of c % pixel is below v, making the $a\%$ of data distributed around the maximum strength e, the $c\%$ of data distributed around the minimum strength k, then the grey value of each modified pixel should be:

$$g(x,y) = \begin{cases} e, & f(x,y) \geq u \\ \dfrac{e \cdot f(x,y) + k \cdot u - e \cdot v - k \cdot f(x,y)}{u - v}, & v < f(x,y) < u \\ k, & f(x,y) \leq v \end{cases} \tag{4}$$

The third way is to carry out morphological operation on the catchment basin markers using a priori knowledge so as to strengthen the markers. There are usually two types of morphological operation — expansion and corrosion. The morphological corrosion can remove the inner space of the marker and reduce under-segmentation; while the morphological expansion will merge the markers nearby so as to reduce over-segmentation.

Expansion operation from structuring element $B$to image A refer to $A \oplus B$, which is defined as follows:

$$A \oplus B = \cup \{A + b : b \in B\} \tag{5}$$

Its equivalent equation is

$$A \oplus B = \cup \{B + a : a \in A\} \tag{6}$$

Corrosion operation from structuring element B to image A refer to $A \odot B$, which is defined as follows:

$$A \odot B = \cap \{A = b : b \in B\} \tag{7}$$

2. **Improved Froth Image Segmenting Method Based on Watershed Transformation.** The improved froth image segmentation method based on watershed transformation will properly apply the above-mentioned optimizing techniques, and search corresponding catchment basins according to different H thresholds set for froths of different sizes. Figure 1 shows a typical froth image containing bubbles of all sizes. Now it will be used to illustrate the improved froth image segmentation method based on watershed transformation.

Step 1. Froth Image Strengthening

The froth image is morphologically high-low-hat filtering transformed, and the lighting value is mapped into the range [0255], making 1% of the data distributed around the gray value 255, and other 1% around the grey value 0.

Step 2. The H-minimum area transformation

As for the catchment basins of 3 different sizes (large, medium, and small), we can search for them respectively in the grey value's range [71, 255], [31, 255], and [11, 255], with 200, 50, 12 being the thresholds, then we get the corresponding large, medium and small catchment basins as shown in Figure 3, 4 and 5.

Step 3. Verification of Catchment Basin Marking

The effectiveness of the catchment basin area is verified, and we found that the effectiveness value ranges respectively from (800, 10000] for large catchment basins, (100, 800] for medium-sized ones, and (3, 100] for small ones. Then we removed the unqualified catchment basin markers.

Step 4. Morphological Re-shaping of the Catchment Basin's Markers

The operation is conducted in the following order:

Morphological corrosion is conducted once for the large catchment basins and 3 times for the medium ones.

Morphological expansion is conducted 3 times for the large basins and 6 times for the medium-sized ones.

Merge the three catchment basin images.

The catchment basins are marked on the merged image, with the results shown in Figure 6.

FIGURE 3. Large catchment basin markers

FIGURE 4. Medium catchment basin markers

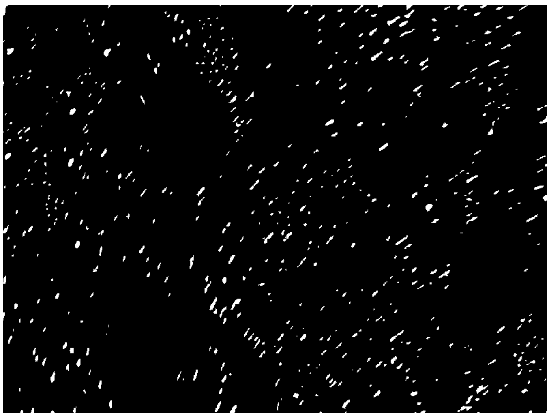

FIGURE 5. Small catchment basin markers

Step 5. Re-construction of the Froth Image

We use the catchment basin markers obtained in Step 4 to carry out morphological re-construction of the froth image, with results shown in Figure 7.

Figure 6. The re-shaping and merging of catchment basin markers

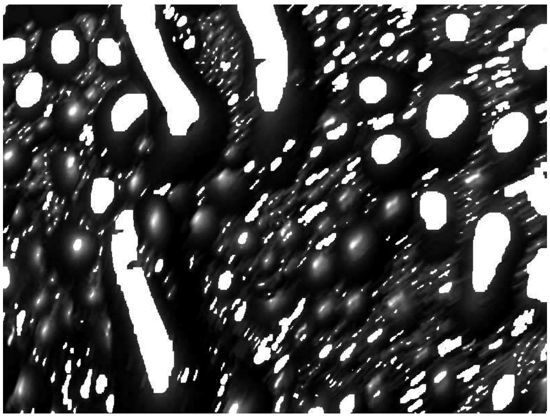

Figure 7. Morphological reconstruction of froth image

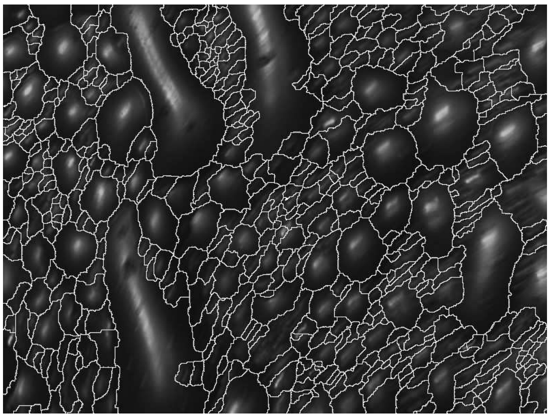

Figure 8. Froth images edge segmentation based on improved watershed transformation

Step 6. Edge Segmentation of Froth Image

Reverse the froth image, then apply watershed transformation to edge-segment the froths, with results shown in Figure 8.

3. Simulation and Analysis.

3.1. Segmenting Experiment for the Froth Image with Big and Small Bubbles. The authors of this paper apply the standard watershed transformation to segment the forth edges as seen in Figure 1, and experiment with various H-minimum area transforming thresholds. The threshold has a great impact on the segmenting results. As shown in Figure 9, when the threshold is comparatively low, a bubble would be divided into several bubbles, with the over-segmentation being increasingly serious especially at the top of the large bubble. As shown in Figure 10, when the threshold is going up, the over-segmentation is decreasing, but the under-segmentation is gradually increasing, finally causing a lot of under-segmentation results in the small-bubbled areas.

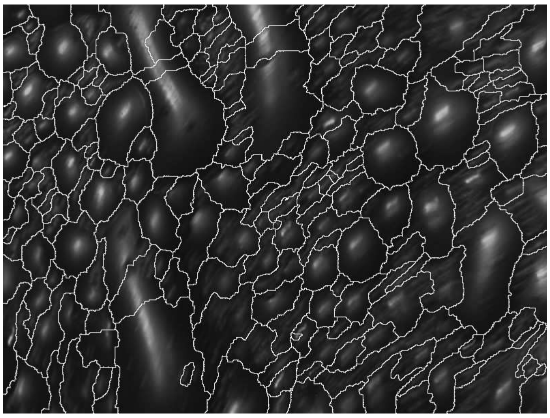

FIGURE 9. Over-segmentation of standard watershed transformation ($h = 20$)

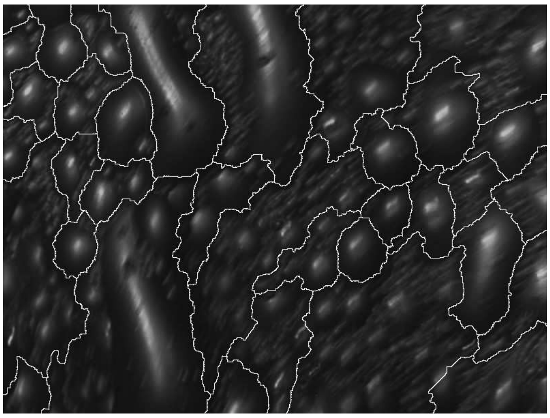

FIGURE 10. Under-segmentation of standard watershed transformation ($h = 100$)

Applying the standard watershed transformation method, the froth edges of Figure 1 are segmented. The results suggest that the best effect can be achieved when the threshold of the H-minimum area is 59, as shown in Figure 11.

The froth edge in Figure 1 are segmented by applying the methods of "gradient transformation + high-low-hat transformation + marker re-shaping + watershed transformation", and the best result is obtained when the threshold of H-minimum area is 61, as shown in Figure 12.

The segmenting effects of Figure 1 is compared with those of the above-mentioned two methods, with the results shown in Table 1.

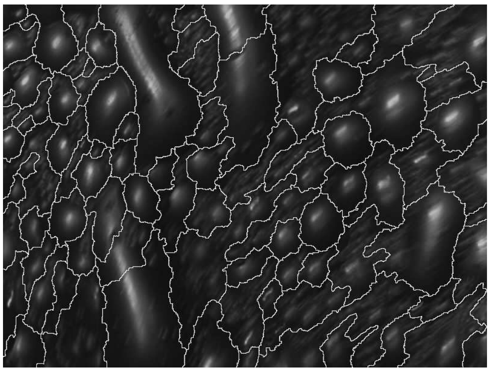

Figure 11. Best segmentation of standard watershed transformation($h = 59$)

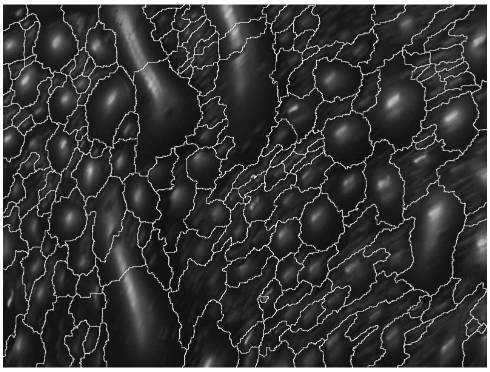

Figure 12. Best segmentation of comprehensive watershed transformation ($h = 61$)

Table 1. Comparison of the best results of different froth image segmentation methods based on watershed transformation.

	Over-segmented area	Under-segmented area	Accurately segmented area	The number of segments
Standard watershed transformation	9.4%	41.5%	49.1%	65
Comprehensive watershed transformation	15.2%	9.7%	75.1%	135
The method proposed in this paper	2.5%	3.3%	94.2%	538

3.2. **The Simulation of Full Sample's Froth Image Segmentation.** A number of froth images chosen randomly from the sample corpus were experimentally segmented by applying standard watershed transformation, comprehensive watershed transformation and the method proposed in this paper, with different results shown in Figure 13.

3.3. **Result Analysis.** (1) Over-segmentation takes place frequently if we use the watershed transformation to segment the froth images; while the standard watershed transformation of the H-minimum area and morphological re-construction are done, the over-segmentation is greatly reduced, which can be seen in Figure 9 and 10 as compared with Figure 2.

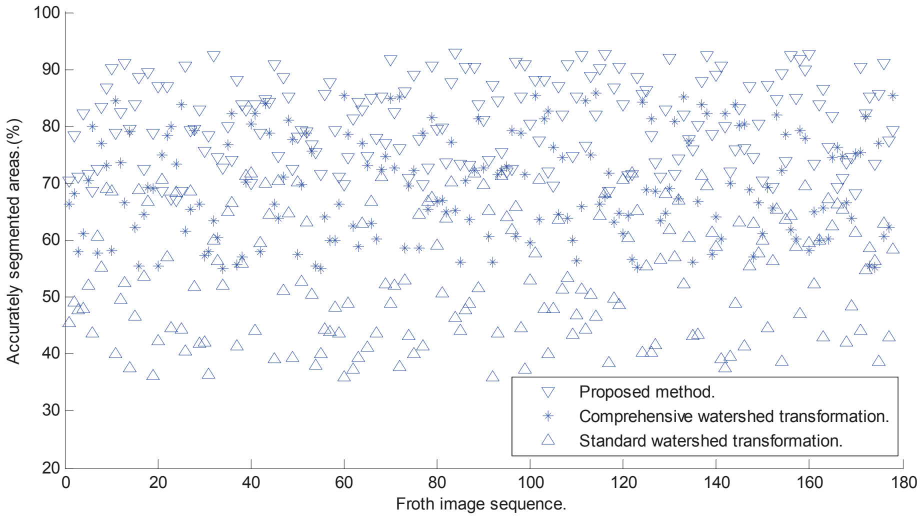

FIGURE 13. Comparison of the accuracy rate of froth image segmentation methods based on watershed transformation.

(2) The size of bubbles is closely related to the segmenting threshold: large bubbles can be more accurately segmented when the threshold is relatively high, while the small bubbles are more accurately segmented when the threshold is relatively low. Therefore, we can't accurately segment the complex froth images with distinctive-sized bubbles at a single threshold. When we conduct a H-minimum area transformation of the froth images, it might remove the weak edge due to the highly set threshold, causing under-segmentation. Figure 9 and 10 show that the segmenting results are especially sensitive to the threshold, meaning over-segmentation at a low threshold and under-segmentation at a high threshold.

(3) As compared with the standard watershed transformation, the comprehensive watershed transformation further improves the segmenting effect. It enhances the recognition value of the froths through high-low-hat transformation, thus reducing the possibility of under-segmentation, improving especially the segmenting effect of small froths. At the same time, the dividing errors are greatly reduced through the application of marker re-shaping technology, thus reducing the possibility of under-segmentation, greatly improving the edge-segmenting effect of large froths. Comparing Figure 11 and 12, we can see that the under-segmentation is greatly reduced in the small-bubbled areas because of the slight increase of over-segmentation thanks to the comprehensive watershed transformation in the large-bubbled areas.

(4) The method proposed in this paper uses different thresholds to search the catchment basin marker in different grey spaces, and solves the problem of un-matching of different-sized froths at a single threshold, so as to achieve a satisfactory effect. Figure 13 shows that the average accuracy rate of the froth image segmentation based on proposed method is 80.68%, which is higher than the comprehensive watershed transformation(69.50%) and the standard watershed transformation(53.84%). When carrying out an edge segmentation of the froth images mixed with different-sized bubbles, the method proposed in this paper is apparently more effective than the traditional methods.

Conclusion. The key to determining the effect of watershed transformation is to accurately mark the catchment basin, while the key to marking catchment basins is to set a proper threshold of the H-minimum area. The improved froth image segmentation method based on watershed transformation is to determine the large froth catchment basin marker at a high threshold, and the small froth catchment basin marker at a low threshold on the basis of gradient transformation, high-low-hat transformation and marker reshaping, greatly impressing the accuracy of catchment basin marking. The experiment results show that the method proposed in this paper has a higher segmenting accuracy and better robustness.

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REFERENCES

[1] G. C. He, K. Q. Huang, Study of the Relation Between Flotation Indexes and Digital Froth Images", *Metal Mine*, Vol. 386, no. 8, pp. 97-101, 2008

[2] T. Wu, Adaptive Rough Entropy Method for Image Thresholding , *Journal of Image and Graphics*, vol. 19, no. 1, pp. 1-10, 2014

[3] C. Cai, P. J. Li, J. G. Guo, Segmentation of High Resolution Imagery over Urban Area Using Watershed Transformation and Stratified Region Merging , *Acta Scientiarum Naturalium Universitatis Pekinensis*, vol. 50, no. 2, pp. 323-330, 2014

[4] J. B. Li, M. Li, J.-S. Pan, S. C. Chu, J. F. Roddick, Gabor-based Kernel Self-optimization Fisher Discriminant for Optical Character Segmentation from Text-image-mixed Document , *Optik - International Journal for Light and Electron Optics*, vol. 126, no. 21, pp. 3119-3124, 2015

[5] C. H. Yang, K. J. Zhou, X. M. Mou, et al., Froth Color and Size Measuring Method for Flotation Based on Computer Vision , *Chinese Journal of Scientific Instrument*, vol. 30, no. 4, pp. 717-721, 2009

[6] H. J. Li, T. S. Qiu, H. Y. Song, J. J. He, Adaptive Separation of Mutually Occluding Traffic Signs Based on Watershed Transformation , *Journal of Dalian University of Technology*, vol. 54, no. 1, pp. 100-105, 2014

[7] M. Zhao, H.-Y. Lin, C.-H. Yang, C.-Y. Hsu, J. S. Pan and Meng-Ju Lin, Automatic Threshold Level Set Model Applied on MRI Image Segmentation of Brain Tno. , *Applied Mathematics & Information Sciences*, vol. 9, No. 4, pp. 1-10, 2015.

[8] G. J. Hay , G. Castilla , M. A. Wulder , et al, An Automated Object-based Approach for the Multi-scale Image Segmentation of Forest Scenes , *International Journal of Applied Earth Observation and Geoinformation*, vol. 7, no. 4, pp. 339-359, 2005

[9] G. C. He, J. N. Feng, Y. P. Wu, X. L. Zheng, Research Status and Advances of Flotation Froth Image Processing Technique , *Nonferrous Metals Science and Engineering*, vol. 2, no. 2, pp. 57-63, 2011

[10] N. Sadr-Kazemi , J. J. Gilliers , An Image Processing Algorithm for Measurement of Flotation Froth Bubble Size and Shape Distributions , *Minerals Engineering*, vol. 10, no. 10, pp. 1075-1083, 1997

[11] SHAO Jianbin, CHEN Gang, Segmentation of Bubble Image Based on Watershed Algorithm , *Journal of Xi'an University of Technology*, vol. 27, no. 2, pp. 185-189, 2011

[12] W. S, Yu, Z. Q. Hou, C. Y. Wang , et al, Watershed Algorithm Based on Modified Filter and Marker-Extraction , *Acta Electronica Sinica*, vol. 39, no. 4, pp. 825-830, 2011

[13] Y. Q. Liu, W. Q. Yuan, J. Y. Guo, On-line Palmprint Recognition Based on Wavelet Decomposition and High-and-low Hat Transformation , *Application Research of Computers*, vol. 28, no. 6, pp. 2355-2357, 2011

[14] Y. M. Hao, F. Zhu, Fast Algorithm for Two-dimensional Otsu Adaptive Threshold Algorithm , *Journal of Image and Graphics*, vol. 10, no. 4, pp. 484-488, 2005

[15] L. Vincent, P. Soille, Watersheds in Digital Spaces: An Efficient Algorithm Based on Immersion Simulations , *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, no. 6, pp. 583-598, 1991

[16] Y. Q. Qu,X. Z. Lin, Z. L. Li, C. H. Wang, An Image Segmentation of Flotation Froth Based on Watershed Transformation , J*ournal of Beijing Institute of Petro-chemical Technology*, vol. 15, no. 1, pp. 61-66, 2007